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Abstract

This paper studies the heterogeneous energy cost and charging demand impact of autonomous electric vehicle(EV) fleet under different ambient temperature. A data-driven method is introduced to formulate a two-dimensional grid stochastic energy consumption model for electric vehicles. The energy consumption model aids in analyzing EV energy cost and describing uncertainties under variable average vehicle trip speed and ambient temperature conditions. An integrated eco-routing and optimal charging decision making framework is designed to improve the capability of autonomous EV's trip level energy management in a shared fleet. The decision making process helps to find minimum energy cost routes with consideration of charging strategies and travel time requirements. By taking advantage of derived models and technologies, comprehensive case studies are performed on a data-driven simulated transportation network in New York City. Detailed results show us the heterogeneous energy impact and charging demand under different ambient temperature. By giving the same travel demand and charging station information, under the low and high ambient temperature within each month, there exist more than 20% difference of overall energy cost and 60% difference of charging demand. All studies will help to construct sustainable infrastructure for autonomous EV fleet trip level energy management in real world applications.

Key words: Energy Impact Evaluation, Energy Consumption Model, Eco-Routing, Charging Decision Making, Autonomous Electric Vehicle Fleet

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1. Introduction

Increasing electric vehicle (EV) usage for accelerating transportation electrification has crucial impacts on greenhouse gas emissions and energy dependency (Palencia et al. (2016); Sioshansi and Denholm (2009); Eberle and Von Helmolt (2010); Armaroli and Balzani (2011)). In order to improve the adoption of electric vehicles, tremendous work is being performed to electrify powertrain systems and the transportation system (Bilgin et al. (2015)). Recently more than 600,000 plug-in vehicles are on road since 2010 market introduction(EDTA (2017)). Accelerating EV adoption may be a key strategy for helping to achieve transportation sustainability. Besides great progress in electric drive systems, autonomous driving technologies are being developed by lots of automakers and high-tech companies. They are trying to put forward the real-world application of self-driving. Furthermore, automotive OEMs are combining autonomous driving technology with electric vehicles. For example, all Tesla cars being produced now have hardware towards full autonomy (Tesla (2016)). General Motors is also testing autonomous driving on its new Chevrolet Bolt (electrek (2017)). Only a few of them are named here. There are several reasons that some self-driving cars will be electric. First are the regulatory reasons, namely efficiency and emission requirements. Then there are important engineering reasons that electric vehicles are easier for computers to drive. And, of course, ride-hailing or ride-sharing services will increasingly make up a higher percentage of daily miles driven, and it will be easier, cheaper and safer to recharge an unmanned car than to refuel one with gasoline. Therefore, car-sharing or car-hailing companies plan to use both electric vehicles and autonomous driving as part of their transportation network. Self-driving technology is an important aspect to improve their service quality and reduce operation cost. Electrified vehicles can help to improve energy efficiency. These two trends will work together to improve the intelligence and sustainability of transportation system.

Accompanying the appearance of autonomous electric vehicle fleet in future transportation system, driving and charging demand pattern will be very different from current electric vehicles. One discovered fact is that autonomous vehicles increase vehicle miles traveled(VMT) by enabling non-drivers and also may gain a decrease in their value of travel time (VOT) as time in the car can be spent on other activities besides driving (van den Berg and Verhoef (2016)). This fact may provide more opportunities for autonomous electric vehicles to make energy-efficient driving strategies. On-board computer systems in autonomous EVs can help them to make most of decisions, for example, routing strategies and charging station selection, etc. Due to strong capabilities of decision making, on-board computation and connectivity in autonomous systems, autonomous electric vehicles have large potential to select energy-efficient routes and to find best locations for charging actions during their itineraries. For electric vehicle fleet management, especially electric vehicles used in ride-sharing, ride-hailing or taxi scenarios, it is valuable to design energy-efficient routing and charging strategies in order to reduce fleet's overall energy cost. Energy-efficient routing and charging will not only increase the sustainability of fleet system, but also reduce the operating cost, e.g. monetary cost for maintenance and purchasing electricity, etc. Energy consumption behavior of autonomous electric vehicle fleet will have much difference due to potential usage of new technologies. It is crucial to understand energy-efficient routing and charging technologies and their energy impact so as to improve the sustainability of future transportation system.

This paper aims to study the energy impact of autonomous electric vehicle fleet under different ambient temperature conditions. In order to achieve this objective, two essential frameworks are developed for energy impact analysis:

First, a data-driven stochastic energy consumption prediction framework for electric vehicles with regard to average vehicle speed within a given trip and temperature. A stochastic model is necessary for energy impact analysis on EV fleet. This model possessing statistical features can generalize various energy consumption behaviors for a fleet of electric vehicles. A gridding method is applied to achieve high-resolution understanding of uncertainties.

Second, an eco-routing and charging decision making framework for autonomous electric vehicle fleet is proposed. Derived strategies can help autonomous EVs to find the minimum energy cost routes and also perform charging actions if necessary. These strategies are designed under several realistic constraints, for example, travel time cost, destination energy requirement and also vehicle driving range, etc. Eco-routing and charging decision making framework can provide a powerful tool of trip level energy management for autonomous electric vehicle fleet.

Therefore, two proposed frameworks work together to simulate energy cost behaviors of autonomous EV fleet and aid in studying potential energy impact under ambient temperature.

The paper is organized as follows. A literature review is provided in Section 2. Section 3 introduces a data-driven grid stochastic energy consumption prediction framework. Section 4 introduces an integrated eco-routing and charging decision making framework. Detailed case studies related to energy impact analysis with regard to ambient temperature are illustrated in Section 5. A conclusion is provided in Section 6.

2. Literature Review

The ultimate objective of this paper is to study and understand energy impact of future autonomous electric vehicle fleet under different ambient temperature. In order to achieve it, two main parts are necessary: an EV energy consumption prediction framework with consideration of average vehicle speed and ambient temperature, and an automated eco-routing and charging decision making framework for EV trip level energy management.

Energy cost prediction for electric vehicles has been studied from two main aspects: the first main methodology is based on vehicle physical model, including tractive effort models (Prins et al. (2013)), power-based energy consumption models (Yi and Bauer (2017, 2016b); Fiori et al. (2016)) and energy consumption model based on generic high-level specifications and technical characteristics (Genikomsakis and Mitrentsis (2017)). The second main methodology utilizes data analysis methods, including feature-based linear regression from historical driving data (Ondruska and Posner (2014)), a systematic energy consumption estimation approach based on driving conditions (Zhang and Yao (2015)), and multiple linear regression methods based on real-world data (De Cauwer et al. (2015); Chen et al. (2017a)). Physical models need high-resolution real-time information to support accurate predictions. This type of model is not a good choice for energy impact analysis on fleet system level, because they lack capability to model uncertainties of energy cost under variety of factors. Most data driven methods in the literature don't involve detailed inner relationships between the energy cost and variety of factors. For example, there are heterogeneous characteristics of different energy consumption components (e.g. propulsion energy cost, regenerative energy, heater and air conditioner energy cost, etc) under various vehicle speeds and temperature. The research in Liu et al. (2017) only explores interactive effects of ambient temperature on overall energy cost. It didn't investigate no detailed modeling of different components and their uncertainties. To our best knowledge, previous methods didn't model uncertainties of energy cost in detail under realistic speed and ambient temperature. These uncertainties are crucial to provide the capability of analyzing potential energy impact under variety of factors in a fleet scenario. Energy consumption model with consideration of uncertainties can generalize and simulate the energy cost behaviors of different EVs(different cars of same make/model) in a fleet. This is the main function of energy consumption model in this paper.

Much research has been done individually for eco-routing or charging decision making. Due to the special characteristics in battery electric vehicles, e.g. limited cruising range, long charge time and sparse coverage of charging stations, lots of work has been introduced to minimize the energy consumption for eco-routing. They have been covered in depth in Abousleiman and Rawashdeh (2014); Sachenbacher et al. (2011); Jurik et al. (2014); Baum et al. (2013); Sweda and Klabjan (2012); Wang et al. (2013); Fontana (2013); Zhu et al. (2017); Yi and Bauer (2018). Most of these research can be divided into two main categories, i.e. Dijkstra-like algorithms and optimization based algorithms. Charging decision making for electric vehicles includes several aspects, e.g. the deployment of charging infrastructure (He et al. (2018); Chen et al. (2017b); Xylia et al. (2017); Yang et al. (2017); Luo et al. (2017a,b); Dias et al. (2017); Yi and Bauer (2016a); He et al. (2015, 2016); Giménez-Gaydou et al. (2016); Frade et al. (2011); Tu et al. (2016); Ghamami et al. (2016); Li et al. (2016); Dong et al. (2014), etc.), the analysis of charging behavior (Hu et al. (2018); Arias et al. (2017); Arias and Bae (2016); Marmaras et al. (2017); Latinopoulos et al. (2017); Yang et al. (2016); Birrell et al. (2015); Smart and Schey (2012), etc.) and the design of charging strategies (Moon and Kim (2017); Zhang et al. (2017); Yagcitekin and Uzunoglu (2016), etc.). The work related to charging decision making in this paper is to design trip level strategies, including charging station selection and amount of charged energy. An intelligent and sustainable way to schedule charging actions is crucial to improve the driving experience and reduce the range anxiety of electric vehicle users. Optimal charging decision making for a personal autonomous vehicle has been discussed in Yi and Shirk (2018). There is some research on charging decision making in fleet management system, for example the work in (Chen et al. (2016a), Pourazarm et al. (2016)). It aims to make sure an EV fleet can always have enough energy to perform services. However, this research doesn't investigate decision making by involving the eco-routing and autonomous driving setting.

With the emerging of autonomous driving and its application in electric vehicles, the charging decision making should be taken over by vehicles. Autonomous electric vehicles will require the capability to make charging decisions according to the battery energy state, the travel demand and also the available charging infrastructure. Automated electric vehicle charging stations will become available in the future (Corbett and Maniaci (2013); Tesla (2017)). Some works have touched this topic under the car-sharing situation. The work in Fagnant and Kockelman (2014) describes the design of an agent-based model for shared autonomous vehicle (SAV) operations. Chen et al. (2016b) further explores the management of a fleet of shared autonomous electric vehicles (SAEVs) in a regional, discrete-time, agent-based model. Although charging actions have been touched, the discussion for charging decision making is relatively simple. They don't combine eco-routing with charging decision making together. This is an important aspect for autonomous EV fleet management and improve the entire system energy efficiency. For an autonomous EV in future car-sharing, car-hailing or taxi fleet, it can be charged on its way to another pick-up location. It is necessary to develop strategies for optimizing both eco-routing and charging decision making simultaneously. Some previous research put efforts on designing the optimal routing and charging for battery electric vehicles, as shown in Pourazarm et al. (2016); Chen et al. (2016a). But they are limited to rough energy consumption models without consideration of traffic and ambient temperature. Their methods didn't involve the heterogeneous charging power, travel time and also energy state requirement. Furthermore, none of these research has performed the energy impact analysis of eco-routing and charging for autonomous electric vehicle fleet.

Our work aims to comprehensively understand the potential energy impact of autonomous EV fleet with eco-routing and charging with regard to ambient temperature. Main contributions are summarized as follows:

- Data-driven two-dimensional grid stochastic energy consumption framework for emulating energy cost behaviors of fleet vehicles under different ambient temperature: This framework is derived based on a historical EV taxi dataset. It has the potential capability to simulate different EV energy cost behaviors in an autonomous EV fleet by taking advantage of data-driven stochastic features.

- Integrated eco-routing and charging decision making framework for autonomous EV fleet by considering travel time and energy state requirement: This framework is used to simulate the driving and charging behaviors in autonomous EV fleet system.

- Data-driven simulated transportation network and fleet travel pattern by using EV taxi's pick-up and drop-off information: The simulated network and patterns are used as case study scenarios for energy impact analysis.
- Energy impact and charging demand analysis under different ambient temperature by using a simulated autonomous EV fleet with proposed eco-routing and charging strategies

3. Data-Driven Two-Dimensional Grid Stochastic Energy Consumption Model

3.1. Nissan Leaf Taxi Data

The data for model development was collected in the Electric Vehicle Pilot Program (Taxi and Commission (2013); INL (2016)). It provided an opportunity for the Taxi and Limousine Commission, Nissan and the taxi industry to gather information (both quantitative data and the personal experiences of real New York taxi passengers, drivers and owners) so that we can evaluate what it would take to bring about successful broader adoption of electric taxis. Several 2012 Nissan Leaf battery electric vehicles were provided to New York City taxi fleets and owner-drivers to use in normal taxi service. Charging infrastructure was available to the drivers. On-board electronic data logged from these vehicles is the basis for the provided results. There are in total five Nissan Leafs in this data collection and these data was collected between June 2013 and February 2015. Other detailed information about this data set can be found in Taxi and Commission (2013); INL (2016). This EV taxi data set is definitely a great opportunity for us to investigate the energy impact of future autonomous EV fleet. Due to essential features of taxi transportation system, even though current vehicles are transferred to autonomous driving systems, they will have the similar travel behaviors that are determined by request demand from customers. This means that we can utilize the pick-up and drop-off information to simulate travel patterns of autonomous fleet. Furthermore, the collected data provides detailed energy consumption information, which is very helpful to construct a comprehensive prediction model for EV energy consumption.

Figure 1 illustrates the average trip-level energy cost per mile with regard to average vehicle speed on each trip segment and also ambient temperature. In the given data set, each trip has its distance information and travel time cost between origin and destination. The average speed value within this trip can be calculated from the distance divided by the travel time. Ambient temperature means the environmental temperature, not the vehicle internal temperature or battery internal temperature. It shows large uncertainties even by giving specific average speed and temperature. However, the collected data has detailed information to aid in constructing a comprehensive energy cost model.

The collected data for each trip segment includes a lot of detailed information. The main features related to trip-level energy cost modeling and energy impact evaluation include trip distance, trip time cost, pickup location, drop-off

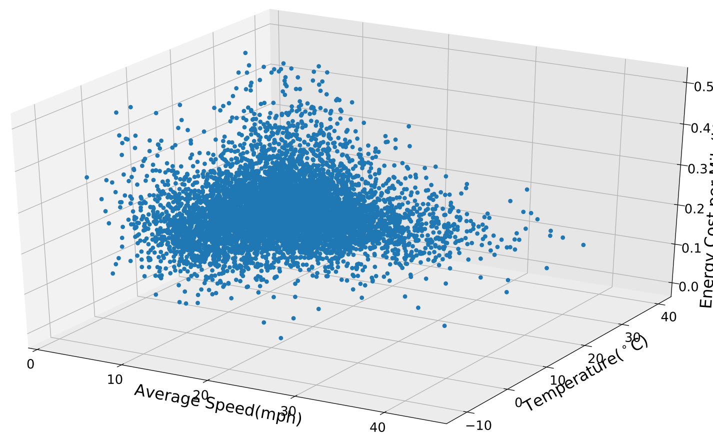

Figure 1: Energy cost per mile of Nissan Leaf Taxi with regard to average vehicle speed and ambient temperature in New York City

location, ambient temperature, overall energy consumption, energy consumption of heating, ventilation, and air conditioning (HVAC), and regenerative energy. The overall energy consumption can be divided into three sub components, i.e. propulsion energy cost, HVAC energy cost and regenerative energy. Energy consumption of electric vehicles depends on variety of factors, e.g. vehicle speed and environmental conditions, etc. Among the environmental conditions, temperature has large effect on EV energy consumption. The ambient temperature will be involved into our modeling procedure. Therefore we have the following equation to describe the energy cost for a given trip:

$$E_{\text{avg}}(v,T) = E_p(v,T) + E_{hvac}(v,T) - E_{reg}(v) \tag{1}$$

where v is the average vehicle speed along the trip and T is the ambient temperature. This is based on detailed physical models of energy consumption in (Yi and Bauer (2017)). Assume that the propulsion energy cost $E_p(v,T)$ and HVAC energy cost $E_{hvac}(v,T)$ depend on both of average vehicle speed and ambient temperature. $E_{reg}(v)$ is the regenerative braking energy. Regenerative braking is an energy recovery mechanism which slows a vehicle by converting its kinetic energy into a form which can be either used immediately or stored until needed. The regenerative braking is a big advantage of electric vehicles to improve the energy efficiency comparing to traditional gasoline vehicles. Equation (1) assumes regenerative brake energy value $E_{reg}(v)$ is positive. $E_{reg}(v)$ mainly depends on traffic condition and is modeled with regard to average vehicle speed. Equation 1 assumes that three energy cost components are independent and all of them contribute to the overall energy consumption. We will provide the detailed models for all three components in the following sections. These stochastic models are created from the real world data. Stochastic model can generate ergodic samples to emulate different situations and then to perform energy impact evaluation on fleet level.

3.2. Multi-Dimensional Gridding Method

The gridding method represents that an entire feasible space consisted of several dependent variables is discretized into a bunch of sub-regions. Data driven methods are performed individually on each sub-region. Each region can be a k-dimensional space, where k is the number of dependent variables. Dependent variables are selected or derived from available dataset. Generally higher resolution of collected data (more specifically, energy consumption information with more related conditions) will aid in providing a more accurate gridding model. The following will provide a general description for gridding method proposed in this paper.

The notation $G^k_{\prod_{i=1}^k n_i}(\mathcal{S})$ is used to represent a specific gridding stochastic model. In this notation, k is the number of dimensions applied in this model. n_i is the number of discretized intervals along the i_{th} dependent variable. A larger value of n_i can have a discretization with high resolution for i_{th} dependent variable. $\mathcal{S}$ represents probability distribution cluster on all grids. Suppose the coordinate of one grid is denoted by $(o_1, ..., o_i, ..., o_k)$, where $1 \leq o_i \leq n_i$. Then the distribution set $\mathcal{S} = \{S_{(o_1,...,o_k)}\}$ has $\prod_{i=1}^k n_i$ different distributions. They are underlying distributions that the data fits within all grids. These distributions can be estimated by using density estimation method. The general density estimation method with underlying density function assumption is utilized in this paper instead of kernel density estimation(KDE). KDE is a nonparametric density estimator requiring no assumption that the underlying density function is from a parametric family. However, it is better to utilize the general density estimation/fitting if an obvious pattern of existing probability density function can be found in the given data. It can provide more accurate model and is easy for us to perform future calculations for sample generation. Figure 2 illustrates an example of $G^2_{n_1 \times n_2}(\mathcal{S})$. It is a 2-D gridding method by considering two different dependent variables where $n_1 = 4$ and $n_2 = 5$ with $|\mathcal{S}| = 20$. Therefore, the entire range of average vehicle speed is divided into four different intervals and the entire range of ambient temperature is divided into five different intervals. In total 20 sub-regions are obtained and their corresponding models can be constructed, e.g. $G^2_{4\times5}(S_{(1,5)})$, $G^2_{4\times5}(S_{(2,4)})$, etc. Each sub-region has a part of data points from the entire original data set. Data points in each sub-region are utilized to estimate the distribution of energy cost per mile within the given average speed and temperature range.

The overall energy cost per mile can be divided into three independent parts: the propulsion energy cost per mile, HVAC energy cost per mile and regenerative brake energy per mile. The trip-level propulsion energy cost mainly depends on

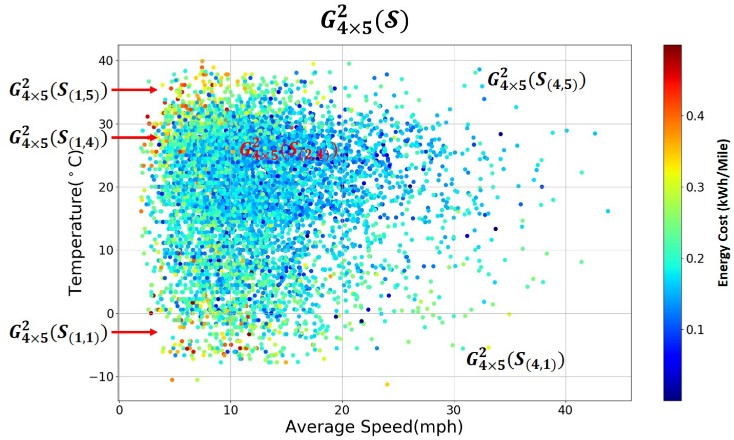

Figure 2: An example of 2-D Gridding Model

the average speed during this trip segment and ambient temperature conditions (Temperature causes variation of powertrain efficiency), so it can be modeled as $G^2_{n_1\times n_2}(\mathcal{S}_p)$. The average vehicle speed and ambient temperature can have large effect on HVAC energy cost. The model for HVAC energy cost per mile can be described by $G^2_{n_1\times n_2}(\mathcal{S}_h)$. However, the regenerative brake energy only mainly depends on the traffic situation, this means that a $G^1_{n_1}(\mathcal{S}_r)$ model with regard to average vehicle speed should be good to describe it. The accuracy of these models depends on the amount of collected available data samples. But they can be improved by continuing to collect data. If these models are utilized to predict energy cost for a specific EV, each specific EV can have its own models. These models can be updated in a real-time and adaptive manner by collecting the unique data of each vehicle itself.

3.3. $G^2_{n_1\times n_2}(\mathcal{S}_h)$ for HVAC Energy Consumption Model

Figure 3 illustrates the energy cost per mile of HVAC(heating, ventilation, and air conditioning) with regard to trip average vehicle speed and ambient temperature. Energy cost of HVAC has heterogeneous patterns under different temperatures and average vehicle speed. Generally, it costs more energy by HVAC under a very low or very high temperature. However, as shown Figure 3, there are huge uncertainties for energy cost per mile and also very different uncertainty distributions under various temperature and average speed values. Due to the consideration of EV Taxi data, one phenomenon is that drivers often turned HVAC off to save energy when no passengers were present. In order to understand such uncertainties and their inherent distribution, the introduced gridding method is applied on the investigated data.

It is clearly indicated in Figure 3 that the HVAC energy cost is influenced by both ambient temperature and trip average speed. Generally, an extreme temperature needs higher HVAC power consumption to maintain a comfortable

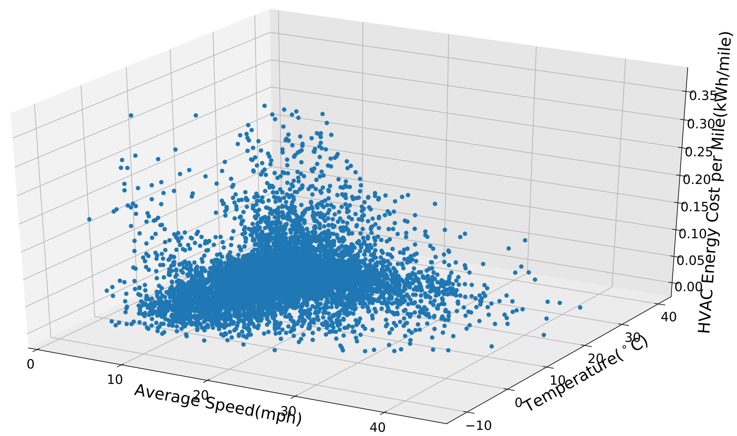

Figure 3: HVAC energy cost per mile with regard to different average speed and ambient temperature

in-vehicle environment. Due to the consideration of energy cost per mile, the vehicle speed, which can determine the travel time cost for each mile, will impact on the value of energy cost per mile. A $G^2_{n_1 \times n_2}(\mathcal{S}_h)$ model is a reasonable choice to provide a description for energy cost behavior of HVAC. Figure 4 shows analysis results of HVAC energy cost based on $G^2_{3\times 3}(\mathcal{S}_h)$ model. This means that both the entire feasible ranges of vehicle speed and temperature are divided into three intervals. Then this model has nine different grids with $|\mathcal{S}_h| = 9$. Each grid includes a subset of data from the entire dataset. Statistic analysis is performed on each grid to get the potential probability distribution for uncertainty description. Histogram analysis and density estimation show us that exponential distribution is a good option to model the energy cost behavior on each grid. This mean $S_{(i,j)} \sim \mathrm{Exp}(\lambda^j_i)$. Of course, each grid has its own exponential distribution with λ^j_i based on real data fitting. These heterogeneous distributions provide comprehensive understanding of energy cost uncertainties. Figure 4 also illustrates average value for HVAC energy cost per mile within each grid. Given a temperature interval, the HVAC energy cost per mile becomes smaller when vehicle speed becomes larger. Two reasons account for this fact: energy cost per mile is a function of time and HVAC power is also a function of vehicle speed, for example, more power to heat when driving faster in very cold air. Given a vehicle speed interval, the energy cost per mile approaches the minimum value around $10°C$ to $20°C$, which is the middle interval in this particular case.

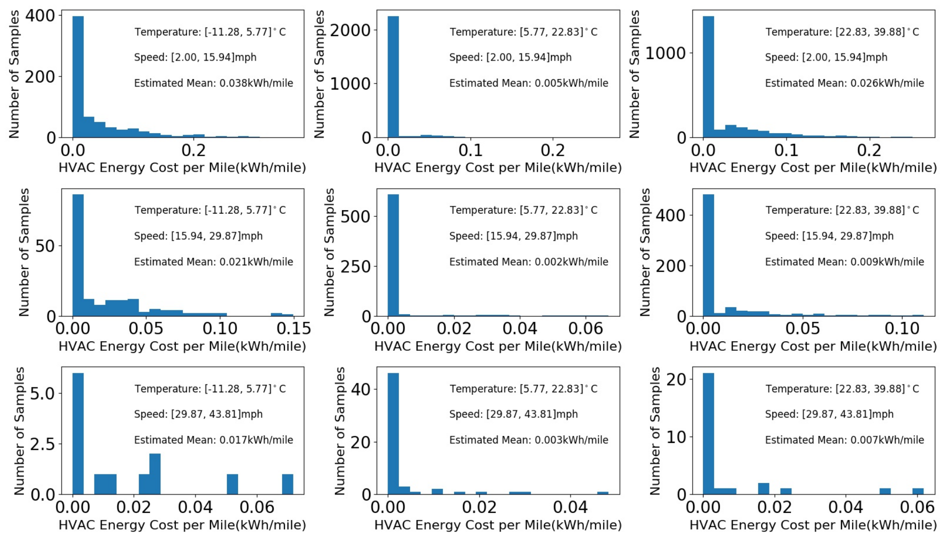

Figure 4: $G^2_{3\times 3}(\mathcal{S}_h)$ model for HVAC energy cost per mile with regard to different temperature and vehicle speeds

What we have in Figure 4 is just a demonstration for our methodology. If more data samples can be collected under different values of average vehicle speed and ambient temperature, the number of intervals along each direction can be increased so as to obtain more grids and then a model with higher resolution for HVAC energy consumption.

3.4. $G^1_{n_1}(\mathcal{S}_r)$ Model for Regenerative Brake Energy

Regenerative brake energy is the energy recovered by the brake regeneration system in EVs. It has little dependence on temperature condition. So it is reasonable to model regenerative brake energy only with regard to average speed over a trip. Figure 5 provides the regenerative brake energy per mile with regard to average vehicle speed. It is easy to see that the average regenerative brake energy per mile decreases when vehicle speed increases. A lower average speed usually results from a city driving with more traffic congestion and regulations. More deceleration operations of EVs occur. These decelerations contribute more to the regenerative energy. However, the regenerative energy has different uncertainties with regard to average vehicle speed. It is valuable to model the uncertainties in order to provide a better representation of random behaviors for regenerative brake energy under given trip average speed.

Regenerative brake energy mainly depends on the traffic situation, which can be indicated by the average vehicle speed in some extent. Therefore, a $G^1_{n_1}(\mathcal{S}_r)$ model can be utilized to describe the regenerative energy behavior. Figure 6

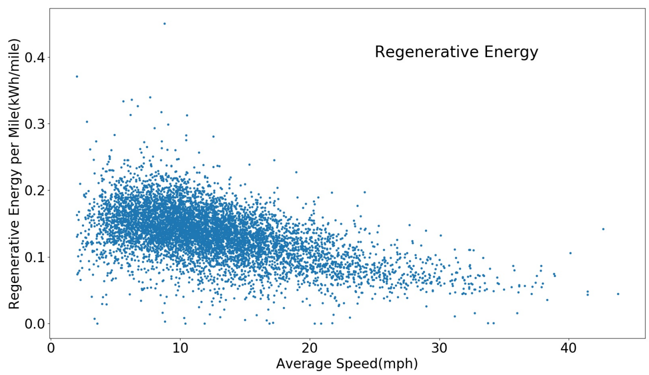

Figure 5: Regenerative brake energy per mile with regard to different average speeds

demonstrates a $G_4^1(\mathcal{S}_r)$ model for regenerative brake energy based on the Nissan Leaf taxi data. The corresponding statistic analysis results are illustrated. Histogram analyses show us that uncertainty of regenerative energy on each grid can be modeled by log-normal distribution, i.e. $S_i \sim \text{Log-Normal}(\mu_i, \sigma_i)$. The density estimation is performed on each grid to obtain key parameters (mean value μ_i and standard deviation σ_i) of log-normal distributions. Different values of mean and variance are obtained on each grid. Generally, the mean value of regenerative brake energy becomes smaller when trip average vehicle speed becomes larger.

The resolution of the introduced model is determined by the number of intervals along the entire range of average vehicle speed and also available data samples within each interval. A dense data set that has abundant samples along the entire average speed range can construct high resolution $G_{n_1}^1(\mathcal{S}_r)$ model by utilizing more intervals, for example larger n_1 and more accurate probability density function estimation.

3.5. $G_{n_1\times n_2}^2(\mathcal{S}_p)$ Model for Propulsion Energy Consumption

Propulsion energy cost of electric vehicles is influenced by traffic condition and also ambient temperature. However, traffic condition can have a key influence on propulsion energy consumption. Ambient temperature has effect on the efficiency of electric powertrain system, especially battery efficiency. Then the temperature provides indirect impacts on propulsion energy consumption. Figure 7 provides scattering plot to describe the distribution of propulsion energy consumption under different ambient temperature and trip average vehicle speeds.

In order to understand heterogeneous features of propulsion energy cost under different vehicle speed and ambient temperature, a $G_{n_1\times n_2}^2(\mathcal{S}_p)$ model is introduced. Figure 8 illustrates a result of $G_{3\times 3}^2(\mathcal{S}_p)$ model based on the Nissan Leaf taxi data. Both of the temperature and vehicle speed range are divided into

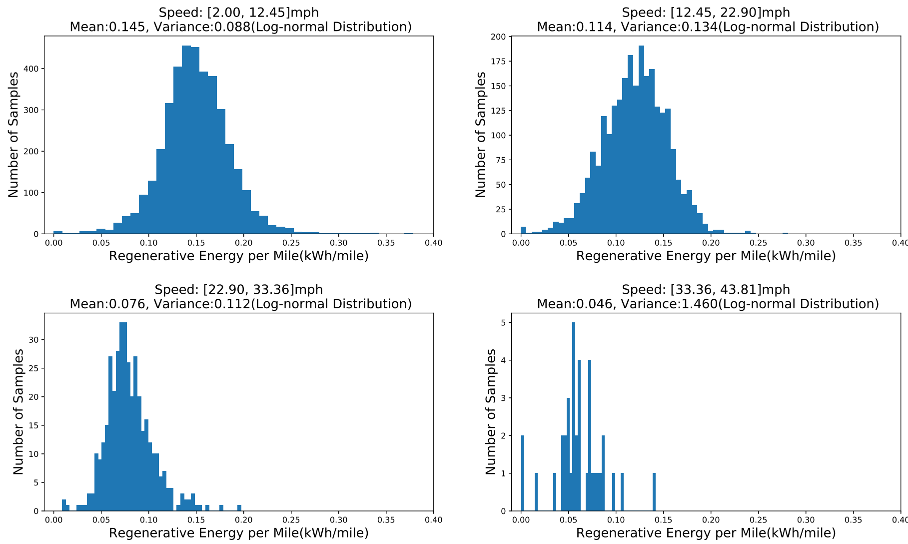

Figure 6: $G_4^1(\mathcal{S}_r)$ model for regenerative energy per mile with regard to different average speeds

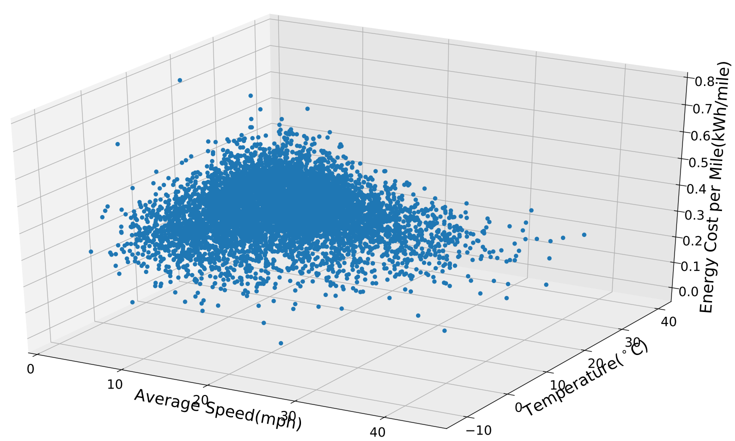

Figure 7: Distribution of propulsion energy cost per mile with regard to average speed and ambient temperature

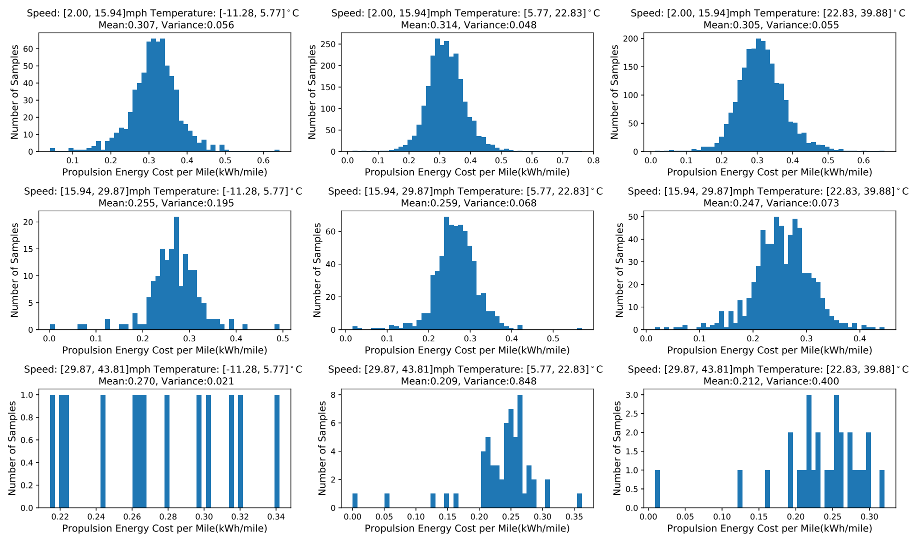

Figure 8: $G^2_{3\times 3}(\mathcal{S}_p)$ model for propulsion energy cost per mile with regard to average vehicle speed and ambient temperature

three subsets, which generates a 3×3 grid network with 9 grids in total. Figure 8 illustrates that energy cost per mile in each grid cell follows a log-normal distribution, i.e. $S_{(i,j)} \sim \text{Log-Normal}(\mu_i^j, \sigma_i^j)$. Density estimation is performed to obtain all log-normal distributions with the corresponding values of mean and standard variance. The provided result doesn't have a good estimation within high speed interval due to small size of samples in Nissan Leaf taxi dataset. However, the proposed methodology is adjustable to fit datasets with different resolutions. As discussions in other grid models, higher resolution dataset with abundant samples along dependent variables can aid in constructing a better grid model with more cells and obtain comprehensive distribution information.

3.6. Grid Stochastic Model for Overall Energy Consumption

Potential distributions can be derived to construct grid stochastic models. The overall energy cost per mile for electric vehicles can be modeled as:

$$\begin{aligned} &\text{Energy Cost Per Mile(kWh/mile)} \\ &= \underbrace{G^2_{k_1\times k_2}(\mathcal{S}_p)}_{\text{Propulsion Energy Cost}} + \underbrace{G^2_{m_1\times m_2}(\mathcal{S}_h)}_{\text{HVAC Energy Cost}} - \underbrace{G^1_{n_1}(\mathcal{S}_r)}_{\text{Regenerative Energy}} \end{aligned} \tag{2}$$

where $G^2_{k_1\times k_2}(\mathcal{S}_p)$, $G^2_{m_1\times m_2}(\mathcal{S}_h)$ and $G^1_{n_1}(\mathcal{S}_r)$ is used to model the energy cost per mile. k_1, m_1 and n_1 are the numbers of intervals for average vehicle speed. k_2

and m_2 are the numbers of intervals for ambient temperature. $\mathcal{S}_p$ is a log-normal distribution cluster with $k_1 \times k_2$ elements in total and $S_i^j \sim$ Log-Normal(μ_i^j, σ_i^j); $\mathcal{S}_h$ is an exponential distribution cluster with $m_1 \times m_2$ elements in total and $S_i^j \sim$ Exp(μ_i^j); $\mathcal{S}_r$ is a log-normal distribution cluster with n_1 elements in total and $S_i \sim$ Log-Normal(μ_i, σ_i). In order to obtain a data-driven grid stochastic energy consumption model for a specific electric vehicle, the following information needs to be determined or learned from the real world data:

- Grid size and number: In proposed models, two different independent variables (i.e. average vehicle speed and ambient temperature) are utilized according to historical data knowledge. The grid size and number is determined by the interval size and number along each dependent variable. Generally, high resolution data can provide more grids with small grid size. The selection of grid size and number in Figure 4, 6 and 8 are just examples for convenience to demonstrate the methodology. More smaller grids are utilized in following case studies in order to construct a higher resolution grid stochastic model for energy impact evaluation.
- Probability distribution within each grid cell: Density estimation is performed in each grid cell based on the assigned distribution format. The assigned distribution is determined according to preliminary analyses. The pre-defined format of potential distribution helps to find more accurate mathematical model to describe uncertainties of energy consumption. Each grid cell has its unique distribution to describe uncertainties of energy cost under average speed and ambient temperature.

Remark: Energy consumption model formulation in this section is derived based on Nissan Leaf Taxi dataset. The obtained specific model parameters can only be used to simulate the energy cost behaviors of Nissan Leaf in New York. However, battery electric vehicles have similar energy cost behaviors. Therefore, the introduced methodology should work for any brand of electric vehicles, which should follow the similar distribution formats as what we analyzed from the data of Nissan Leaf in Equation (2). Parameters for distributions and grid size and number depend on available data for specific electric vehicles.

4. Eco-Routing and Charging Decision Making

Autonomous electric vehicle fleet has great potential applications in ride-sharing, ride-hailing or taxi system, as discussed in Introduction section. An autonomous electric vehicle fleet system can be managed by central system controllers in the future. A central controller should make sure the controlled EVs always have enough energy to complete customers' service request and they will not spend time on charging when customers are on board. Therefore, central controller should have the capability to collect real-time information, for example, availability, energy states and customers' travel request, etc. Central controllers will optimize their operations to find the best available EV to satisfy a travel request. The selected EV will travel to the requested pick-up location under a given time constraint. If an EV is idle and has lower energy state, a charging action is necessary before its next pick-up action. Scheduling algorithms and central controller design are not the focus of our paper. We will study control strategies in our future work. In this paper, assume that central controllers exist and EVs can receive commands that include origin and destination information, energy state requirement for next trip and maximum travel time requirement. Our paper focuses on designing optimization models and algorithms to help autonomous EVs find the best energy efficient routing and charging strategies(i.e. charging station selection, amount of charged energy) by considering constraints received from central controllers.

4.1. Optimal Decision Making Model

We consider a road network modeled as a directed graph $G = (\mathcal{N}, \mathcal{A})$ with $\mathcal{N} = 1, ..., n$ and $|\mathcal{A}| = m$. Node $i \in \mathcal{N}$ represents a node in the road network. It can be a normal node or a node with charging station. $(i, j) \in \mathcal{A}$ is an arc(link) connecting node i to j. We also define $I(i)$ to be the set of start nodes of arcs that are incoming to node i and define $O(i)$ to be the set of end nodes of arcs that are outgoing from node i. They are $I(i) = \{j \in \mathcal{N} | (j, i) \in \mathcal{A}\}$ and $O(i) = \{j \in \mathcal{N} | (i, j) \in \mathcal{A}\}$. For each arc $(i, j) \in \mathcal{A}$, there are two cost parameters: the required traveling time t_{ij} and required energy consumption e_{ij} on this arc. Note the $t_{ij} > 0$ (if nodes i and j are not connected, then $t_{ij} = +\infty$). E_{ij} is allowed to be negative due to potential energy recuperation effect. E_{ij} depends on traffic and ambient temperature.

Here we are interested in a single-origin-single-destination vehicle routing problem. Assume the origin is node o and destination is node d. Denote the selection of arc (i, j) by $x_{i,j} \in \{0, 1\}$, $i, j \in \mathcal{N}$. P_i is the charging power at node i. If node i has no charging station, we set $P_i = 0$, otherwise P_i is determined by the charging level(e.g. Level 2 charging station with $P_i = 6.6$kW and DC fast charging station with $P_i = 50$kW). t_i is the time when arriving at node i. The introduced model assumes to know the initial time at origin t_o and the required latest time at destination t_d. This information provides the time constraint in the routing and charging decision making. Denote t_c^i as the charging time cost at node i. Usually $t_c^i = 0$ if there is no charging station at node i. E_i is the energy state at node i before charging action. E_i needs to be less than the battery capacity C_p. We have the lower bound of energy requirement E_{req} at destination node d. For all E_j, $j \in O(i)$, we have

$$E_j = \sum_{i \in I(j)} (E_i + t_c^i P_i - E_{ij}) x_{ij}, \quad x_{ij} \in \{0, 1\} \tag{3}$$

The problem objective is to determine a path from origin o to destination d, as well as recharging time at each intermediate charging station node, so as to minimize the total energy cost by satisfying the travel time and final energy state requirements. We formulate an optimization problem as follows:

$$
\begin{aligned}
&\min_{x_{ij}} \sum_{i=1}^{N}\sum_{j=1}^{N} E_{ij}x_{ij} && \text{(4a)}\\
\text{s.t.}\quad & \sum_{j\in O(i)} x_{ij} - \sum_{j\in I(i)} x_{ji} = b_i && \text{(4b)}\\
& b_o = 1,\ b_d = -1,\ b_i = 0 \ when \ i \in \mathcal{N}/\{o,d\} && \text{(4c)}\\
& E_j = \sum_{i\in I(j)} (E_i + t_c^i P_i - E_{ij})x_{ij} \quad j \in \mathcal{N}/\{o\} && \text{(4d)}\\
& t_o + \sum_{i=1}^{N}\sum_{j=1}^{N} t_{ij}x_{ij} + \sum_{i=1}^{N} t_c^i \le t_d && \text{(4e)}\\
& E_{lb} \le E_i \le C_p && \text{(4f)}\\
& 0 \le t_c^i \le MP_i && \text{(4g)}\\
& x_{ij} = 0 \ \text{ or } \ 1 && \text{(4h)}\\
& E_d \ge E_{req} && \text{(4i)}
\end{aligned}
$$

The objective function (4a) is the overall energy cost for selected route. The constraints (4b) and (4c) stand for the flow conservation, which implies that only one path starting from node i can be selected, i.e. $\sum_{j\in O(i)} x_{ij} \le 1$. $b_o = 1$ means there is no incoming arc for the origin. $b_d = -1$ means there is no outgoing arc for the destination. Constraint (4d) represents the vehicle's energy dynamics. It provides the energy state transition from the node i to node j. The energy state at origin assumes to be known. Constraint (4e) is the overall time constraint for the selected route. The summation of travel time cost and charging time cost should be smaller than $t_d - t_o$, which is the given time cost upper bound. Constraint (4f) provides the lower bound and upper bound of battery energy state at each node i. The lower bound E_{lb} describes the lowest energy level that vehicles can reach before charging actions. It is straight forward that upper bound is the battery capacity C_p. Constraint (4g) provides bounds for charging time and illustrate the charging behavior at node i. M is a large positive number. The upper bound of charging time at node i is determined by charging power. If $P_i = 0$(no charging station at node i), then $MP_i = 0$ makes sure that no charging action occurs at node i. Constraint (4i) is the energy state requirement at destination, it should be larger than E_{req}. E_{req} is determined by the energy requirement of next delivery service. It may be larger than the energy state at origin.

In Equation (4), the objective function is a linear function. We have the required decision variables x_{ij}s and t_c^is. x_{ij}s are binary variables. Constraint (4d) is a nonlinear function. all other constraints are linear constraints. Therefore, the proposed decision making model is a mixed integer nonlinear programming problem. Many commercial or open source solvers can be used to solve Equation (4), e.g. CPLEX, SCIP, etc. We utilize the SCIP to provide optimal routing and charging decision making for following simulations and case studies.

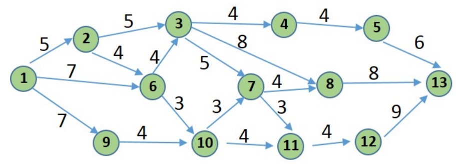

Figure 9: A simulated road network

The overall decision-making process includes two steps: First, get the necessary road network between the origin and destination and calculate the energy cost on road segment under variety of factors, e.g. traffic, temperature, road grade and powertrain type, etc. Second, populate and solve the optimal decision-making model in Equation (4) based on the road network and energy cost information. Therefore, the functionality of introduced optimal decision-making model is independent to energy related realistic conditions.

In order to get an eco-routing strategy, all related information is necessary to be input at the beginning of decision making. From this aspect, the proposed eco-routing algorithm is under static assumption. However, it is convenient to consider the dynamics of traffic information by performing eco-routing decision making in a receding horizon manner. We can run the introduced eco-routing algorithm for each time step. Before rerunning this algorithm, the current vehicle location information and latest traffic information can be obtained to calculate the up-to-date travel time and energy consumption on each road segment. By using these real-time information, this eco-routing model can provide new routing strategies within each time step. The length of time step is determined by the dynamics of real-time traffic information. This type of receding horizon decision making strategy is applied in most of existing routing engines. Our proposed model can also use the same strategy to improve its dynamical and real-time features.

4.2. Functionality Simulations

This section will utilize a simple road network in Figure 9 to demonstrate the utility of introduced decision making model in Equation (4). The difference of optimal routing and charging strategies under various requirements and situations are checked.

There are 13 nodes and the corresponding arcs as shown in Figure 9. For each arc, the distance information is provided by using the unit of mile. The origin is node 1 and destination is node 13. We only focus on the algorithm functionality here. More detailed case studies are in the following section. Assume that electric vehicles with battery capacity $24kWh$ have constant speed of $40mph$ on each arc and have the constant energy consumption model of $0.3kWh/mile$. If we don't have the charging requirement or time constraint, the optimal routing strategy should be the same as that obtained by minimum distance algorithm. We have the following six different simulated cases and their results are shown in Figure 10.

Case 1: There is no charging station in the simulated road network. EV has the enough initial energy of $20kWh$ at original node 1. We don't make constraint for the required energy at destination node 13. Therefore, this case is equivalent to the minimum distance routing. We have the optimal result as shown in Figure 10. The final energy state at node 13 is $12.8kWh$. This case can be used as a base line to show the difference when other constraints are required in the decision making process.

Case 2, Case 3 and Case 4: A DC fast charging station is located at node 3, 7 and 11, respectively. They have maximum charging power of $50kW$. The initial energy state at original node 1 is $10kWh$. The required energy state at destination node 13 is at least $20kWh$. So it is necessary to charge the vehicle to make sure it has the required energy state at destination. The energy states at origin and destination are selected randomly. Any other values work for this simulation. We just use an energy state value at destination which is larger than that at origin to check the functionality of charging decision making in the proposed algorithm. The results show that they have different optimal routing strategies. The vehicle takes $t_c^3 = 0.344h$ at node 3 in Case 2, $t_c^7 = 0.35h$ at node 7 in Case 3 and $t_c^{11} = 0.362h$ at node 11 in Case =4, respectively, to perform charging action in order to satisfy the energy demand. The different locations of charging stations cause the difference of optimal routing and potential charging time.

Case 5 and Case 6: Two charging stations with different charging levels are located in the road network. The charging station at node 3 is a Level 2 charging station with maximum charging power of $6.6kW$. The charging station at node 10 is a DC fast charging station with maximum charging power of $50kW$. In both cases, we assume the initial energy state is $10kWh$ and required energy state at destination is at least $20kWh$. In Case 5, we assume that the overall travel and charging time cost must be less than $2h$. In Case 6, the overall travel and charging time cost can be less than $5h$. Based on the different time cost requirements, we have obtained different optimal strategies. When EV has enough time to get the energy in Level 2 charging station, it will select the route with less overall energy cost.

5. Case Studies for Energy Impact Evaluation

In this section, the functionality of eco-routing and charging framework will be studied by using real-world data. Based on pick-up and drop-off information in the collected New York EV taxi dataset, a transportation network and simulated travel patterns will be constructed for case studies. According to the introduced stochastic energy consumption models for electric vehicles, comprehensive case studies will be performed to investigate potential heterogeneous energy impact (including energy cost and charging demand) of autonomous EV fleet under different ambient temperature conditions.

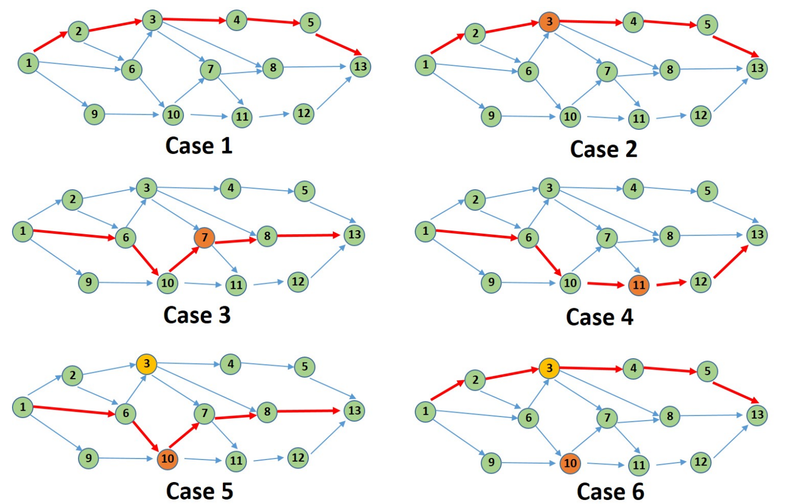

Figure 10: Optimal routes for six different simulation cases

5.1. Transportation Network for Case Studies

Figure 11 illustrates the longitude and latitude information of all pick-up locations in New York EV taxi dataset. We can see that most of pick-up locations are in Manhattan. The drop-off information is not provided here, because both of pick-up and drop-off locations have very similar patterns, especially in Manhattan area. Case studies in this section only focus on the area of Manhattan. The pick-up location information is detailed enough to represent appearance locations of EV fleet in Manhattan area. These location information can help to construct the nodes in the transportation network. The dataset only provides the trip information with pairs of pick-up and drop-off location. In order to analyze the energy impact, a connected itinerary with several trip segments is necessary for each EV in the fleet. This is because we need to investigate the energy consumption and charging behavior. Only a long itinerary can be taken to have both enough energy cost and charging necessity. It has no way to directly utilize pairs of pick-up and drop-off locations from given data set to construct the required transportation network. It is necessary to process these location information so as to obtain an elegant transportation network that can be cooperated with introduced eco-routing and charging decision making models.

K-means clustering algorithm is utilized to find centroids of all locations in Figure 11 for transportation network construction. This clustering algorithm creates some centroids to represent the nearby location information. There are 20 centroids from k-means algorithm shown in Figure 11. We will only consider the 15 centroids in Manhattan area in our case studies. The specific latitude and longitude information for these 15 centroids are shown in Table 1. The number of centroids is determined by the requirement of number of road network nodes

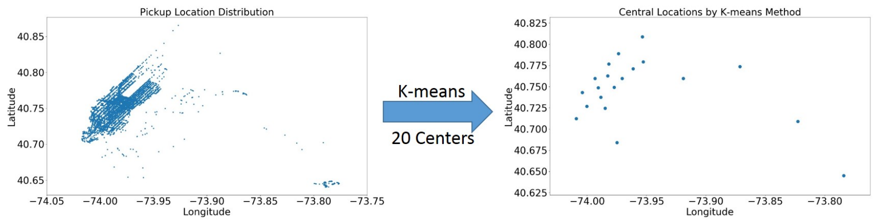

Figure 11: Clustering of pick-up locations

Table 1: Longitude and latitude information of centroids

Node	(LONG, LAT)	Node	(LONG, LAT)	Node	(LONG, LAT)
1	(-74.009,40.712)	2	(-74.004,40.743)	3	(-74.000,40.727)
4	(-73.993,40.760)	5	(-73.991,40.749)	6	(-73.988,40.738)
7	(-73.985,40.724)	8	(-73.983,40.763)	9	(-73.977,40.749)
10	(-73,982,40.777)	11	(-73.970,40.760)	12	(-73.974,40.789)
13	(-73.961,40.771)	14	(-73.953,40.779)	15	(-73.953,40.809)

in the transportation network. In our case studies, a transportation network with 15 nodes supposes to be applied. Larger number of road network nodes can describe more detailed of transportation patterns.

Figure 12 illustrates the obtained 15 centroids on the Google Maps of Manhattan. It also provides the location information of two realistic DC fast charging stations in Manhattan, which are Node 16 and 17. There are a lot of Level 1 and Level 2 charging stations in this area and EVs can perform charging actions in them. However, only the autonomous electric vehicle taxi fleet is considered in our case studies. DC fast charging stations help the autonomous EV fleet reduce charging time and increase available service time. Assume that all charging actions will be scheduled to these two charging stations according to the introduced eco-routing and charging decision making algorithm. During following simulations, only the location information of two existing public DC fast charging station is utilized and these charging stations are assumed to have unlimited service capability. In reality, for a small autonomous EV fleet equipped with two large charging stations, maybe it works for all charging requirements. When the size of autonomous EV fleet increases, the number of charging stations are required to increase simultaneously in order to reduce the time cost of charging actions. Following results are only used to demonstrate the functionality of introduced algorithms and models. They are preliminary results to understand the energy and charging demand of future autonomous EV fleet. In order to simulate more realistic situations, more detailed modelings not only for autonomous vehicles but also for charging infrastructure system, are necessary in the future work.

We have introduced a transportation network for our case studies in Figure 12. Distance values of arcs in Figure 12 are obtained by using Google Maps.

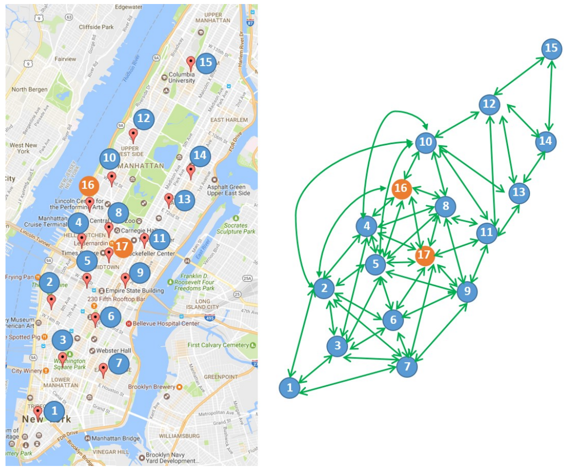

Figure 12: A simulated road network for energy impact evaluation of autonomous EV fleet in New York City

We utilize the Google Maps APIs to determine the realistic driving distance between a pair of origin and destination. We take use of input O-D information and use the Directions API with "driving" mode in Google Maps APIs to obtain the corresponding driving distance, which is determined by the route that has the minimum driving distance from all provided alternative routes in Google Maps. However, responses of Google Map API depends on when the query is made. Different time may get different response results. In following simulations, an average value of driving distance for each pair of origin and destination pair is utilized. This average value is obtained by making queries under several different time slots within a day. This is because simulations in this paper focus on the effect of ambient temperature and a transportation network with constant but realistic driving distance can reduce effects from other factors. It is good choice to understand the effect only from the ambient temperature.

5.2. Case Studies of a Single Trip

Case studies of a single trip have been performed to demonstrate the functionality of the introduced eco-routing and charging decision making framework. Detailed conditions and corresponding results for several cases are shown in Table 2. Two O-D (Origin-Destination) trips with two different energy requirements are investigated. We can see that totally different optimal routes are selected. When an EV has enough energy to finish the requested trip and satisfy the requirement at destination at the same time, for example, as shown in Scenario 2, the optimal route with minimum energy consumption will not go through charging station node. However, if the energy requirement at destination is high, it is necessary to perform a charging action during the routing. From Scenario 1, we have seen that both of optimal routes include charging

Table 2: Results for single trip studies

	Scenario 1 $E_o = 10kWh$ $E_d \geq 20kWh$	Scenario 2 $E_o = 20kWh$ $E_d \geq 10kWh$
(Origin,Destination)	Optimal Route	Optimal Route
(1, 15)	1→2→**16**→10→12→15 Charged energy:15.68kWh	1→2→10→12→15 Charged energy:0kWh
(13,7)	13→11→**17**→6→7 Charged energy:11.5kWh	13→11→9→7 Charged energy:0kWh

station nodes. Even though they have the same final energy state requirement, different energy has been charged due to their energy cost on different routes.

5.3. Generation of Itineraries

In order to study the energy impact of energy cost and charging demand, a long itinerary for each EV in the fleet should be considered. The EV taxi data that we have can help to generate itineraries by appropriate statistical analysis. In order to generate reasonable itineraries, we have constructed the occurrence probability model in Figure 13 and vehicle speed distribution in Figure 14. The occurrence probability model describes how often or in what probability EVs appear in each centroid. It is the analysis result of pick-up distribution at each centroid based on k-means method from EV taxi data. The probability distribution can be used to keep the occurrence of each node in generated itineraries. For example, more itineraries of EV taxis may include location 7 due to the maximum occurrence probability. Figure 14 shows the probability density function of average speed of each road segment in Manhattan area. This distribution is based on real average speed in the EV taxi data set. Due to the heavy traffic in Manhattan area, the average vehicle speed is very low. By using this model, a randomly generated speed value is assigned on each road segment. However, the distribution model for average vehicle speed in Figure 14 cannot provide exact speed information on each specific road segment. Only statistic features of vehicle speed distribution can be preserved. This works for a system level simulation.

We utilize procedures in Algorithm 1 to generate itineraries for case studies. An itinerary here consists of several consecutive trip segments. Each trip segment has an origin-destination pair. Algorithm 1 can generate a set of itineraries for a fleet with N_v autonomous electric vehicles. The itinerary for each EV has N_T trip segments. The output of Algorithm 1 is a connection matrix C_M with dimension $N_v \times N_T$. Each row in C_M represents a simulated itinerary for one autonomous vehicle. Each element represents the assigned visited location during an itinerary. The first column in C_M includes origins for all vehicles' itineraries. The constructed distribution models in Figure 13 and 14 are utilized to generate samples for next destination and average vehicle speed on each O-D trip segment.

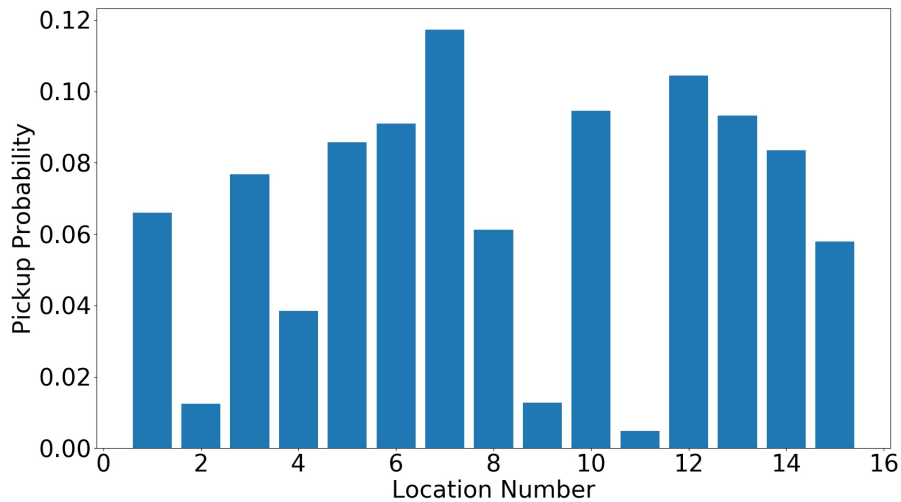

Figure 13: Occurrence probability at each centroid(road node)

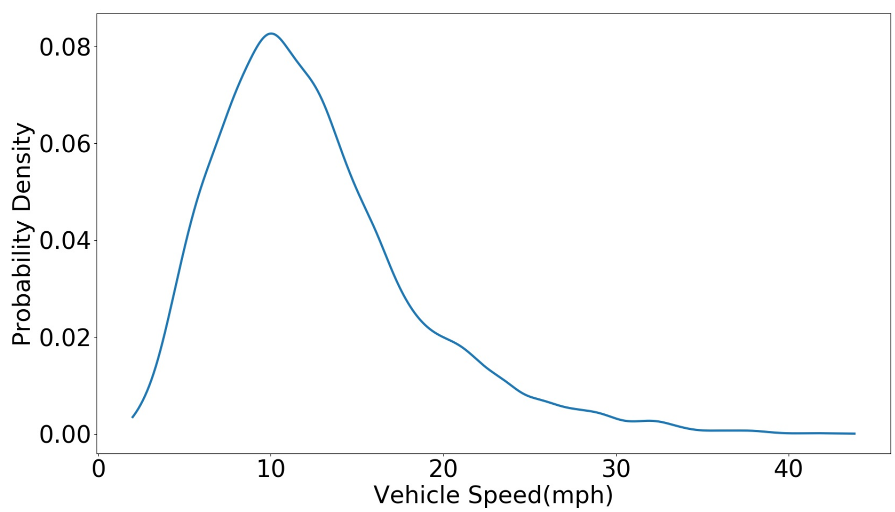

Figure 14: Probability density function of average vehicle speed in Manhattan area

Algorithm 1: Itinerary Generation

Input: Vehicle Number: N_v, Trip Segment Number: N_T
Output: $N_v \times N_T$ connection matrix: C_M
for $i = 1 : N_v$ **do**
  $C_M(i, 1) =$ Sample(Occurrence Probability Model)
for $i = 1 : N_v$ **do**
  for $j = 2 : N_T$ **do**
    TmpNode = Sample(Occurrence Probability Model)
    while $TmpNode == C_M(i, j-1)$ **do**
      TmpNode = Sample(Occurrence Probability Model)
    $C_M(i, j) =$ TmpNode

5.4. Energy Impact Evaluation on Ambient Temperature

By using the introduced transportation network and simulated itineraries, an energy impact evaluation with regard to ambient temperature has been investigated. Figure 15 provides both of overall energy cost and charging demand for both charging stations at Node 16 and 17 under different ambient temperature. Figure 15 is obtained by studying itineraries of 100 EVs(an itinerary for each EV has 100 trip segments) generated according to Algorithm 1. EVs make decisions of routing and charging for each trip segment according to the introduced eco-routing and charging decision making framework. Assume the initial energy state at the beginning of each itinerary is $20kWh$. After a trip segment is finished, if the energy state is less than $5kWh$, EVs need to perform charging actions during the next trip and make sure the energy state goes back to at least $20kWh$. Here the low bound of $5kWh$ is just an example in our case studies. In real situations, this lower bound is determined by the realistic average travel demand for trip segments and also charging station locations. The initial energy state and lower bound for recharged energy state, i.e. $20kWh$, is determined by the EV battery capacity. Nissan Leaf is used in our studies, so a bound of $20kWh$ is utilized.

Results in Figure 15 illustrate that both overall energy consumption and charging demand vary much under different ambient temperature conditions. The energy consumption and charging demand are smallest around 10^oC to 20^oC. Much more energy is consumed under the cold and hot weather. This is due to HVAC energy consumption and also the powertrain efficiency. Meanwhile more charged energy is necessary because of more energy consumed. Generally, the charging demand of Node 17 is larger than that in Node 16. We don't consider the capacity of charging station and assume charging stations can satisfy all charging requirements. Under this assumption, derived results show that charging stations in a specific transportation network receive different charging demand requests. This kind of difference is determined by the mobility pattern of autonomous EV fleet. It is valuable and important to understand the difference of charging demand at different charging stations. Obtained results can help to determine the charging capability of charging stations, e.g. number of

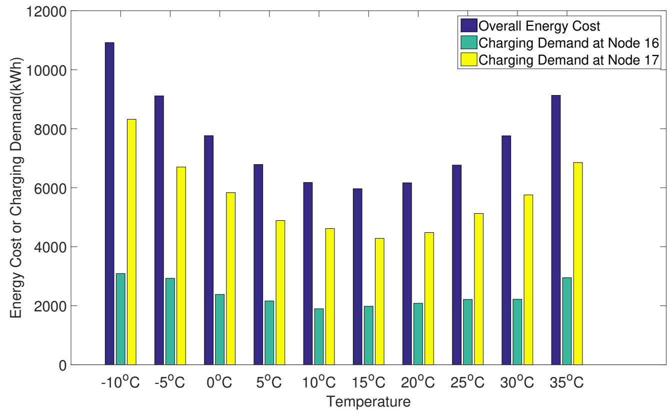

Figure 15: Overall energy cost and charging demand under different ambient temperature

Table 3: Temperature information in New York City

Month	Temperature(°C) (Low, High)	Month	Temperature(°C) (Low, High)
Jan	(-3.1, 3.8)	Feb	(-1.9, 5.5)
Mar	(1.9, 9.9)	Apr	(6.9, 15.7)
May	(12.6, 21.5)	Jun	(17.7, 26.3)
Jul	(21, 29.3)	Aug	(20.3, 28.4)
Sep	(16.3, 24.4)	Oct	(10.1, 18.3)
Nov	(5.1, 12.3)	Dec	(-0.1, 6.6)

charging points and maximum charging power, etc., and also understand the impact on power grid.

A more valuable evaluation of energy impact for autonomous EV fleet is to study the energy cost and charging demand with regard to different time period, because different time may have different temperature in a long time scale. It is worthy seeing the energy impact trend along different months in a whole year. Table 3 provides the average low and high temperature within each month in New York City. We utilize the same settings, for example, the same number of vehicles and itineraries with the same travel patterns. We study the energy impact under different ambient temperature values within each month. In following results, overall energy cost or charging demand has three different values within each month, i.e. values of energy cost or charging demand under low and high temperature and the average value of these two obtained energy cost or charging demand.

Figure 16 illustrates the overall energy consumption under average lower temperature and high temperature within each month. The corresponding average overall energy consumption in different months is provided too. From the results, it is obvious to notice that EV fleet has much smaller energy con-

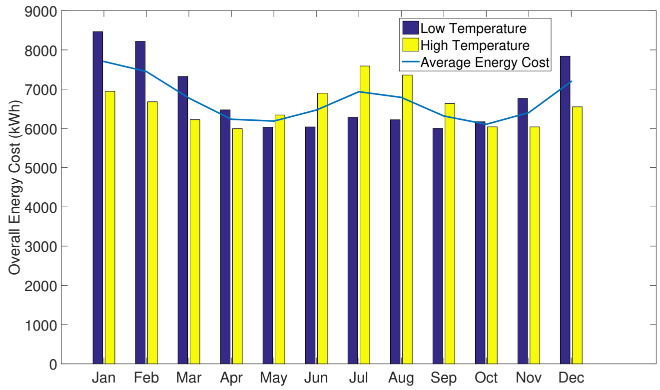

Figure 16: Overall energy cost within each month for a given transportation demand

sumption in April and October. This is due to the mild temperature in April and October. According to the introduced energy consumption model, more energy is needed under very low or high temperature because of energy cost from HVAC. The less requirement of HVAC usage under mild temperature results in much less overall energy demand in these two months. Therefore, EVs in months with very low temperature consume more energy by the same fleet due to the more demand and higher power of HVAC usage. Cold weather has bigger effect on energy consumption of autonomous EV fleet.

Figure 17 and 18 illustrate the charging demand in charging stations of Node 16 and 17, respectively. Like the overall energy consumption, both results provide the charging demand at average low temperature and high temperature within each month. The average charging demand within each month is calculated, respectively. For charging station Node 16, it has smaller charging demand in April and September. For charging station Node 17, it has smaller charging demand in May and October. These charging demand valleys result from small energy demand in April, May, September and October as shown in Figure 16. The overall charging demand in these two charging stations should equal to the energy demand within each month. Both charging stations demonstrate heterogeneous charging demand patterns. Generally charging station Node 17 receives more charging demand than charging station Node 16. Since we assume that both charging stations have the same features, e.g. charging power and enough charging points for all charging requests, the difference of charging demand is caused by the specific locations of charging stations and also the realistic travel patterns of autonomous EV fleet. This is because that the introduced charging decision making algorithm selects charging station and decide the amount of charged energy according to locations of charging stations and current battery energy state. The location difference of these two charging stations and energy demand within different months make Node 16 and 17 have

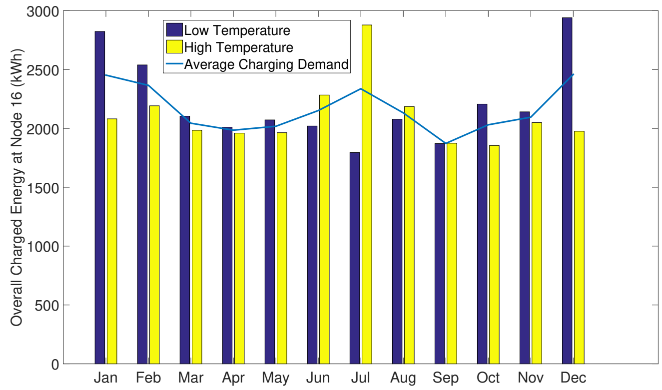

Figure 17: Charging demand distribution at node 16 within each month for a given transportation demand

various dynamic charging demand patterns.

In order to understand how large the effect of ambient temperature condition on energy and charging demand, we look into the difference in percentage within each month between high and low temperature. We propose the following equation to calculate the difference in percentage within each month.

$$\text{Percentage} = \frac{\text{Max\_value} - \text{Min\_value}}{\text{Min\_value}} \times 100\% \tag{5}$$

where Max_value and Min_value are the maximum and minimum values of energy cost or charging demand under both low and high temperature within each month, respectively.

Figure 19 illustrates all percentages for overall energy cost and charging demand within each month. For overall energy cost, the maximum difference in percentage is around 20%, which occurs in very cold or very hot weather. Patterns of charging demand in these two charging stations are very different. The dynamics of charging demand along different months in Node 16 is much larger than that in Node 17. The maximum difference in percentage can reach about 60%. This kind of difference should be a huge challenge for energy supply of charging station. In our simulations, only two DC fast charging stations Node 16 and 17 are utilized. The temperature change causes different energy cost patterns. The difference of energy demand results in different charging strategies that are derived by the introduced charging decision making algorithm. The charging strategies may select very different charging stations and then cause the imbalance between the charging demand in Node 16 and 17. Sometimes most of them select the same charging station to perform charging actions. This imbalance consecutively results in heterogeneous charging demand patterns in these two charging stations and even some large peak values as shown in Figure 19.

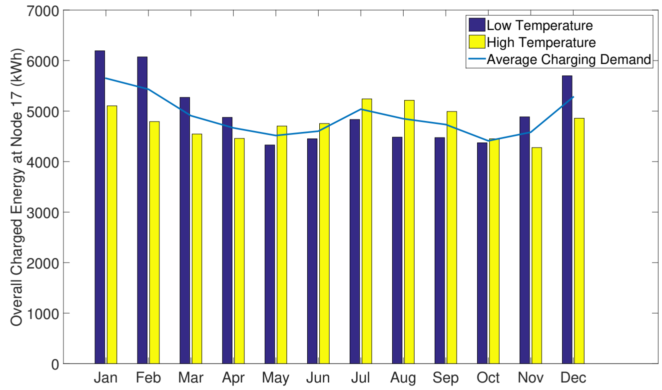

Figure 18: Charging demand distribution at node 17 within each month for a given transportation demand

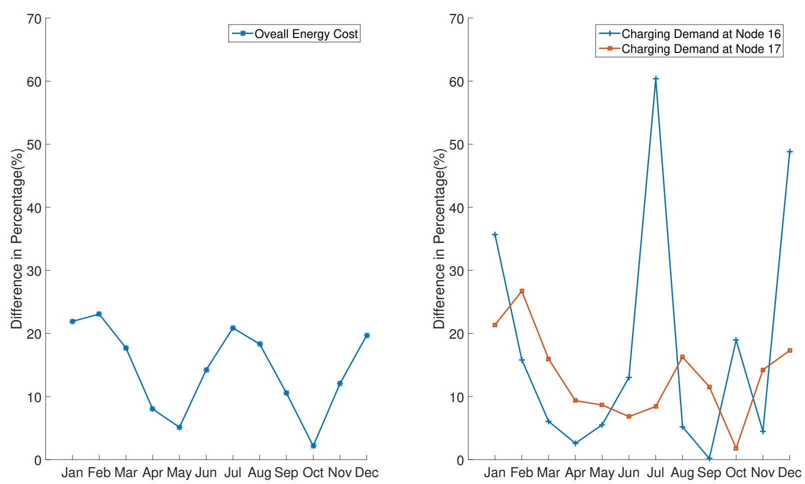

Figure 19: Difference in percentage for overall energy cost and charging demand within each month

All results demonstrate that, even though the travel demand and pattern is the same, the energy cost and corresponding charging demand is very heterogeneous within different months along the whole year. All results show that ambient temperature plays a very important role in energy cost and charging demand in the electrified transportation system, especially for the autonomous electric vehicle fleet that has high dynamics of mobility.

6. Conclusions

Energy impact and charging demand have been evaluated under different ambient temperature for future autonomous electric vehicle fleet. All data-driven models are derived and studies are performed based on a New York Nissan Leaf Taxi dataset. One of the fundamental work is a data-driven grid stochastic energy consumption model with regard to trip average vehicle speed and ambient temperature. This model aids in emulating heterogeneous energy consumption behaviors of vehicles in an autonomous EV fleet. The proposed eco-routing and charging decision making framework has potential to be applied in autonomous EV fleet to improve transportation efficiency. This decision making framework is used to simulate driving activities for autonomous fleet. Results from case studies show a large impact of ambient temperature on energy consumption and charging demand. Potential impact illustrates challenges to optimally balance the energy supply from grid and dynamic energy need from autonomous EV fleet. Proposed methods in this paper provide capabilities to understand potential challenges and aid in designing promising sustainable control strategies in future fleet management.

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